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RESEARCH ON THE UTILIZATION OF PATTERN RECOGNITION TECHNIQUES TO IDENTIFY AND CLASSIFY OBJECTS IN VIDEO DATA

TECHNICAL PROGRESS REPORT NO. 4
COVERING PERIOD FROM
30 JULY 1966 THROUGH 31 JANUARY 1967

PREPARED UNDER CONTRACT NAS 12-30
FOR THE

NATIONAL AERONAUTICS & SPACE ADMINISTRATION
ELECTRONICS RESEARCH CENTER
CAMBRIDGE, MASSACHUSETTS

ASTROPOWER LABORATORY
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MISSILE & SPACE SYSTEMS DIVISION
DOUGLAS AIRCRAFT COMPANY, INC.
SANTA MONICA/CALIFORNIA

DOUGLAS

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Newport Beach, California

FOREWORD

This report was prepared by Astropower Laboratory of Douglas Aircraft Company, Inc., Newport Beach, California, in fulfillment of NASA contract NAS 12-30. The work was sponsored by the NASA Electronics Research Center, Cambridge, Massachusetts. Mr. Eugene M. Darling, Jr. was the Technical Officer for this office.

The studies began on June 18, 1965. This document is the fourth technical report.

Work on the contract was performed by the Electronics Department of Astropower Laboratory. Dr. R. D. Joseph is the Principal Investigator. Contributors were C. C. Kesler, W. B. Martin, A. G. Ostensoe, and S. S. Viglione.

SUMMARY

This report covers Items 4 and 5 under contract NAS 12-30. These items are concerned with improving the generalization performances achieved in earlier experiments by manipulations of the patterns, and by augmenting known properties with statistically derived properties.

Generalization percentages have been improved significantly, with performances over 92 percent having been recorded for four of the five recognition tasks. For the remaining task, performance was raised to 84-1/2 percent. It is felt that the generalization figures are commensurate with the quality of the patterns — that is, the equal of the performance of human observers dealing with the digitized patterns.

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1.0 INTRODUCTION

The purpose of this project is to examine the feasibility of utilizing pattern recognition techniques as a means for both extracting significant information from pictorial data, and for reducing the total amount of data which must be transmitted in order to convey this information.

Five classification tasks were used to examine the effectiveness of a number of recognition system design techniques. These studies were described in detail in Technical Reports 2 and 3. For convenience, a very brief summary of the results obtained is given in Section 2.0 of this report.

In Section 3.0, additional experiments on the lunar data are reported. The purpose of these experiments was to improve the generalization performance on two of the tasks, and to investigate the decision basis on the third. Pattern manipulation was the principal tool in these experiments.

Section 4.0 presents the results of new combinations of techniques applied to the NIMBUS data. For both recognition tasks, networks utilizing both logically and statistically derived property filters were designed.

2.0 SUMMARY OF PREVIOUS RESULTS

One of the major objectives of the work presented in this report was to improve the generalization results achieved under Tasks 2 and 3. The performance figures obtained previously were reported in detail in Technical Reports 2 and 3. To facilitate comparison with the new data, the generalization performances obtained earlier are summarized in this section.

Two types of data were used — lunar data and NIMBUS data. The lunar data were divided into four classes:

1. Craters without central elevations
2. Craters with central elevations
3. Ridges
4. Rima (or Rilles)

To separate these classes, three recognition tasks were defined:

Task CvC — separate the craters without elevations from those with elevations.

Task RvR — separate the ridges from the rima.

Task CvR — separate the craters from the ridges and rima.

The NIMBUS data were divided into three classes:

1. Noncumulus cloud cover
2. Cumulus solid cells
3. Cumulus polygonal cells

To separate these classes, two additional recognition tasks were defined:

Task NvC — separate the noncumulus from the cumulus cloud cover.

Task PvS — separate the solid from the polygonal cells.

For each of the seven pattern classes, 1000 sample patterns were obtained for use in the statistical design of the recognition systems. Additional sets of 200 patterns of each class were obtained for testing the recognition systems. The patterns used to represent the composite groups — cumulus, crater and ridge-rima — were obtained by choosing half of the combined samples of the appropriate classes.

The lunar patterns were recorded on a 50 by 50 raster and the NIMBUS patterns on a 75 by 75 raster. For each of the three lunar tasks, a set of 310 statistically derived property filters was designed; and for each NIMBUS task, a set of 400 statistically derived property filters was obtained. Each property detector had seven input connections, and used a quadratic switching surface to produce a binary output.

Six adaptive techniques were then used to design decision mechanisms for each property filter set. The performance of the resulting 30 systems on the 400 independent test patterns for each task is given in Table I.

The generalization sample of 200 patterns for each class is derived by taking several translations and rotations of each pattern in a smaller set of basic patterns. For the NIMBUS pattern classes, there were 50 basic patterns for each class, with four "looks" at each. The composite cumulus group (P and S) consisted of two looks at each of 100 basic patterns. By combining the discriminant values for all of the looks at a basic pattern, one may arrive at an estimate of the degree of dependence of the system on location and orientation of the patterns. The multilook system may be implemented by actually taking multiple looks at a test pattern, or by expanding the size of the property filter set. The multilook generalization performances are given in Table II. (Note: The figures for error correction, mean square error, and MADALINE have not been reported earlier.)

TABLE I

GENERALIZATION PERFORMANCES FOR 30 SYSTEMS PERCENTAGE CORRECT DECISIONS

Adaptive Technique	Task				
	Lunar Features			Cloud Features	
	CvC	RvR	CvR	NvC	PvS
Forced Learning	62.8	71.0	74.8	81.2	81.0
Bayes Weights	63.8	75.2	77.5	82.5	82.0
Error Correction	59.8	70.2	99.2	85.8	83.0
Iterative Design	59.0	73.8	99.5	86.2	85.5
Mean Square Error	43.0	74.5	82.2	78.5	80.8
MADALINE	58.0	75.8	84.2	86.0	85.5

TABLE II

MULTILOOK GENERALIZATION PERFORMANCES
PERCENTAGE CORRECT DECISIONS

Adaptive Technique	Task NvC		Task PvS	
	Original	Multilook	Original	Multilook
Forced Learning	81.2	84.7	81.0	86.0
Bayes Weights	82.5	83.3	82.0	86.0
Error Correction	85.8	92.0	83.0	87.0
Iterative Design	86.2	88.7	85.5	89.0
Mean Square Error	78.5	88.7	80.8	85.0
MADALINE	86.0	88.3	85.5	87.0

3.0 LUNAR DATA

This section describes additional experimentation which was performed on the lunar data. The primary tool consisted of manipulating the patterns themselves. For Task CvR (craters vs. ridges-rima), on which 99.5 generalization performance had been obtained, the patterns were scrambled in an attempt to determine the basis for this high performance. For Task RvR (ridges vs. rima), a set of artificial, noise-free patterns was generated for the system design, with the system test being performed on real patterns. For both Tasks RvR and CvC (craters with vs. craters without central elevations), design and testing was conducted with reduced aperture sizes, using 25 by 25 and 15 by 15 subsections selected from the original 50 by 50 patterns.

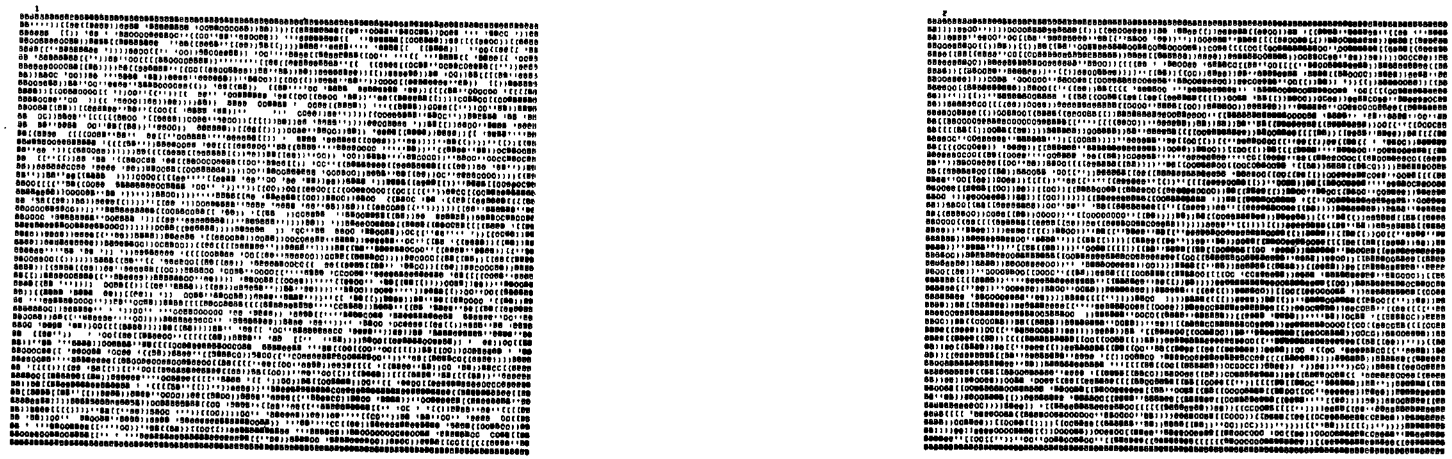
The property filter sets for these experiments were generated by a new computer program (designated QSID) written for the SDS 930. Several of the computational shortcuts which had caused problems in the older IBM 7094 program were eliminated. This has resulted in fewer property filters being required for linear separability of the sample patterns. Two other changes are significant: each property filter now has six input connections, and on each program pass, 15 property filters are designed, with five being selected for inclusion in the system.

3.1 Scrambled Patterns

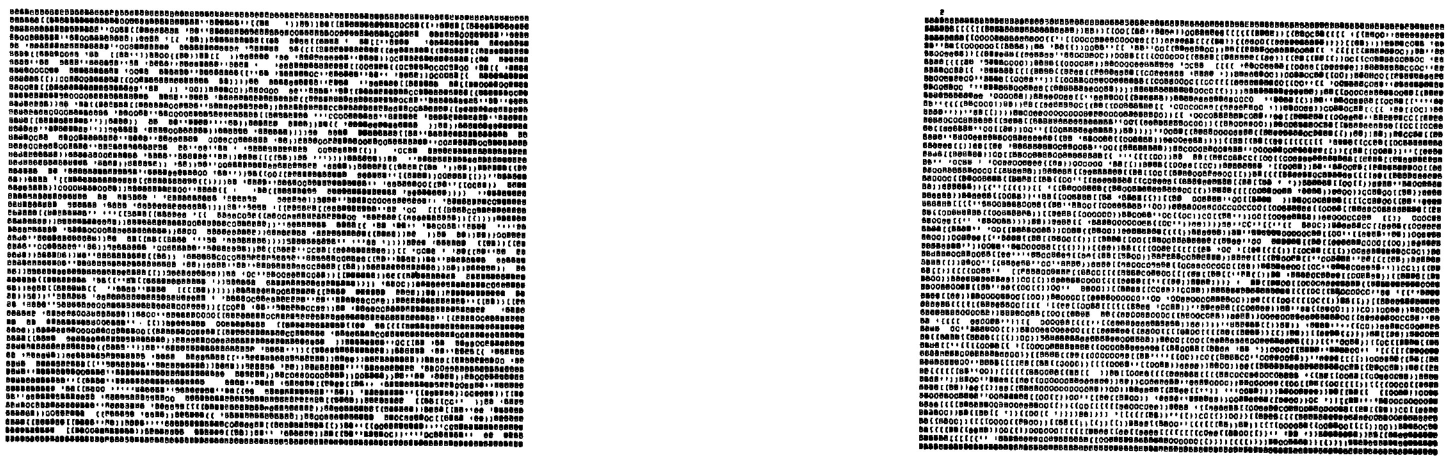
On Task CvR, the very high percentage of 99.5 correct decisions was obtained for both the crater and the ridge-rima groups. It was speculated that the system achieved this by detecting the presence or absence of the distinctive crater formations, with little or no emphasis on the detection of the less prominent ridges and rima.

To test this hypothesis, each of the 400 test patterns for this task was scrambled. Each of the 2500 picture points in a pattern was randomly repositioned in a 50 by 50 raster. Since all of the original picture points are used in the scrambled picture, the gray scale distribution of each pattern remains unchanged. A different random map was used for each picture. Four examples of the random patterns are shown in Figure 1.

The scrambled generalization patterns were then used to test the system. If the conjecture that only the craters were being recognized was



Craters



Linear Features

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Figure 1. Scrambled Patterns

correct, one would expect nearly all of the 400 patterns to be classified as ridges-rima, as none of them have any resemblance to a crater. Additionally, performances greater than chance in both categories would indicate that at least part of the decision depends upon gray scale distribution. This test gains its validity from the high performance levels achieved on the unscrambled patterns.

The results of this experiment are shown in Table III. The final entry in that table, "Best Generalization," represents the highest level of performance achieved during the recursive design of the decision mechanism using the Iterative Design technique. (The design was accomplished on the unscrambled training patterns, of course.) The results clearly show that the system recognizes patterns of both classes, and that the differences in gray scale distribution do not contribute to the recognition process.

3.2 Artificial Patterns

On the two remaining lunar tasks, the performances obtained earlier were less satisfactory. One obvious explanation lies in the signal-to-noise ratio. For Task CvC, on which the poorest performance was achieved, the signal, or significant feature is the (presence or absence of the) central elevation. Even in the most prominent examples, this feature occupies less than one percent of the aperture. For Task RvR, the significant feature occupies less than five percent of the aperture. On this task, the signal is often further weakened when the shadow part of the feature blends in with the background gray level.

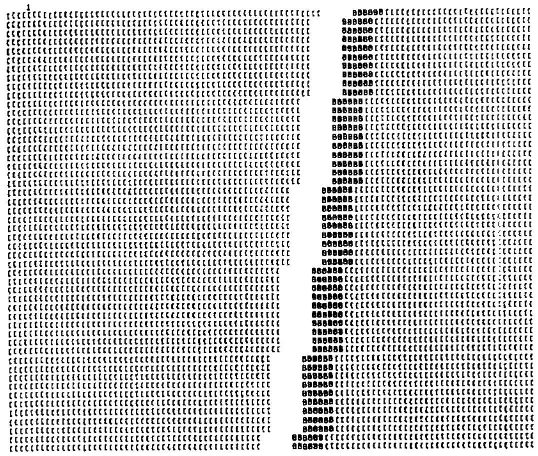
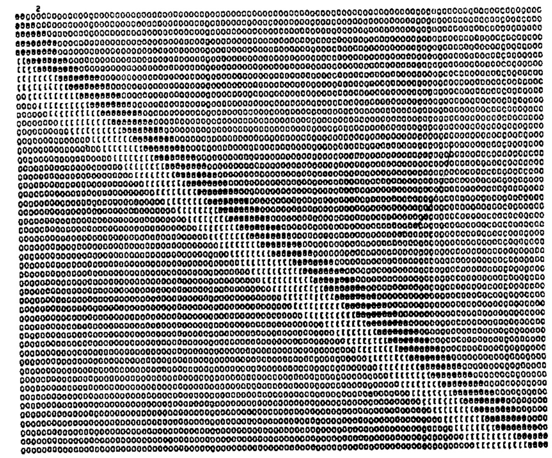
In one attempt to improve performance on Task RvR, a set of artificial, noise-free training patterns was generated. The artificial patterns consisted of a uniform gray background, on which was imposed a pair of adjacent stripes, one lighter, and one darker than the background gray level. Complementary pairs of ridge and rima patterns were generated, the ridge pattern having the lighter stripe on the right, and the rima having the lighter stripe on the left. Two such pairs are shown in Figure 2.

A relatively casual examination of the real patterns was used to establish ranges for the parameters of the artificial patterns. For the angle of the stripes, a trimodal distribution with a range of ±64 degrees (from the

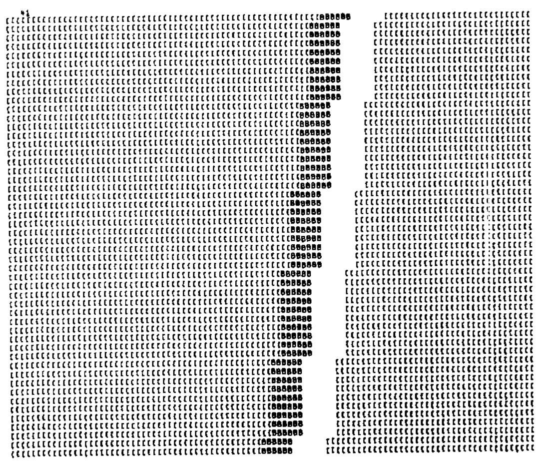
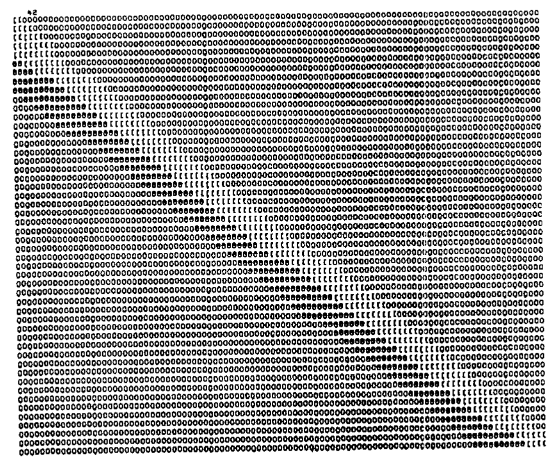
TABLE III

CRATERS VS. LINEAR FEATURES
ITERATIVE DESIGN GENERALIZATION

	Craters	Linear Features	Total
Normal Patterns	99.5	99.5	99.50
Scrambled Patterns	51.5	49.0	50.25
Scrambled Patterns Best Generalization	51.5	52.5	52.00

Rima

Ridges

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Figure 2. Artificial Patterns

vertical) was used. The center of the pattern used a uniform distribution with a range of ±5 raster elements from the center of the aperture. The distribution of the three gray levels was most heavily concentrated toward the darker end of the scale. From these parameter distributions, 1000 pairs of artificial ridges and rima were generated.

Networks were designed to give perfect separability of the artificial patterns, and the performance of these networks was tested on the (real) generalization patterns. The performances achieved are given in Table IV. It is clear that this experiment was a failure, since the best network only provides 60.5 percent performance, compared with the 75.75 percent achieved when real patterns were used for training. The probable cause of this failure is inadequate parameter distribution.

3.3 Reduced Aperture Patterns

In a second approach toward improved signal-to-noise ratios, reduced scanning apertures were used. Subapertures of 15 by 15 and 25 by 25 were applied to each sample lunar pattern, training and test. The subapertures were positioned to include as much as possible of the significant features of the patterns.

Figures 3 through 6 give examples of the 25 by 25 and 15 by 15 patterns. The effect of reducing the aperture is greater on the craters than on the ridges and rima. This is because part of the ridges and rima are sacrificed as the aperture size is decreased, while none of a central elevation is lost. The craters with elevations thus gain quadratically with aperture size reduction, while the ridges and rima gain only linearly.

Results for Task RvR using the 25 by 25 aperture are given in Table V. As with all networks designed in this quarter, 100 percent classification of the training patterns was achieved with the three recursive techniques used (Error Correction, Iterative Design, and MADALINE). The networks used 260 property filters. This is the number of filters that the QSID program (the SDS 930 version of the DAID program) needed to completely separate the training patterns. Later results in this section, and in Section 4.0, indicate that a somewhat smaller set of these units would probably be adequate for complete training pattern separability, and a still smaller set would likely

TABLE IV

ARTIFICIAL RIMA VS. RIDGES (50 x 50), 280 QSID UNITS

Technique	Classification %	Generalization %
Forced Learning	92.40	58.75
Bayes Weights	93.75	58.50

	Total Cycles	For Best Classification			For Best Generalization		
		Class. %	Gen. %	Cycles	Class. %	Gen. %	Cycles
Error Correction	322	100.00	53.75	322	100.00	53.75	322
Iterative Design	6	100.00	58.50	5	98.10	59.25	1
MADALINE	21	100.00	58.75	21	96.10	60.50	3

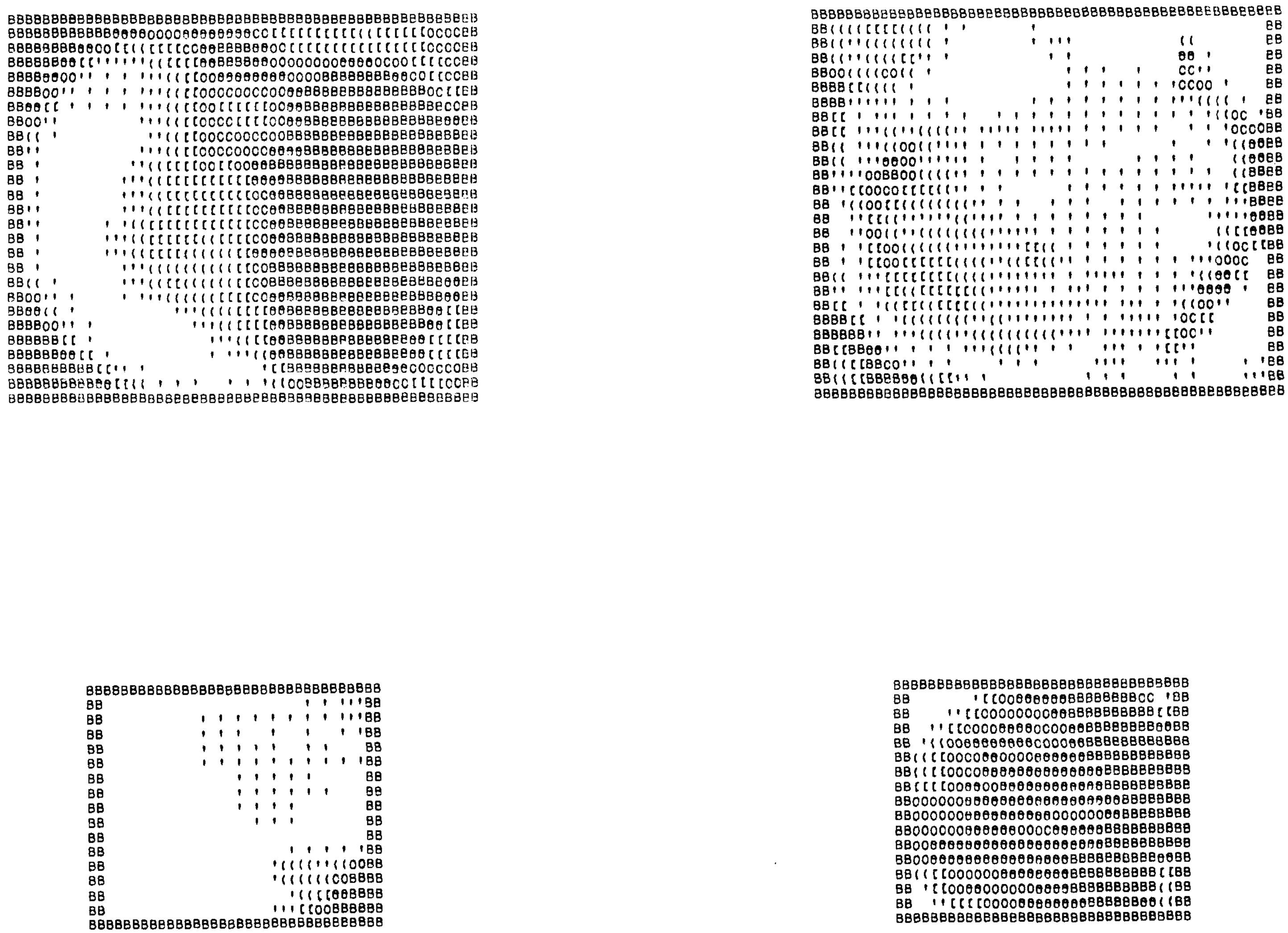

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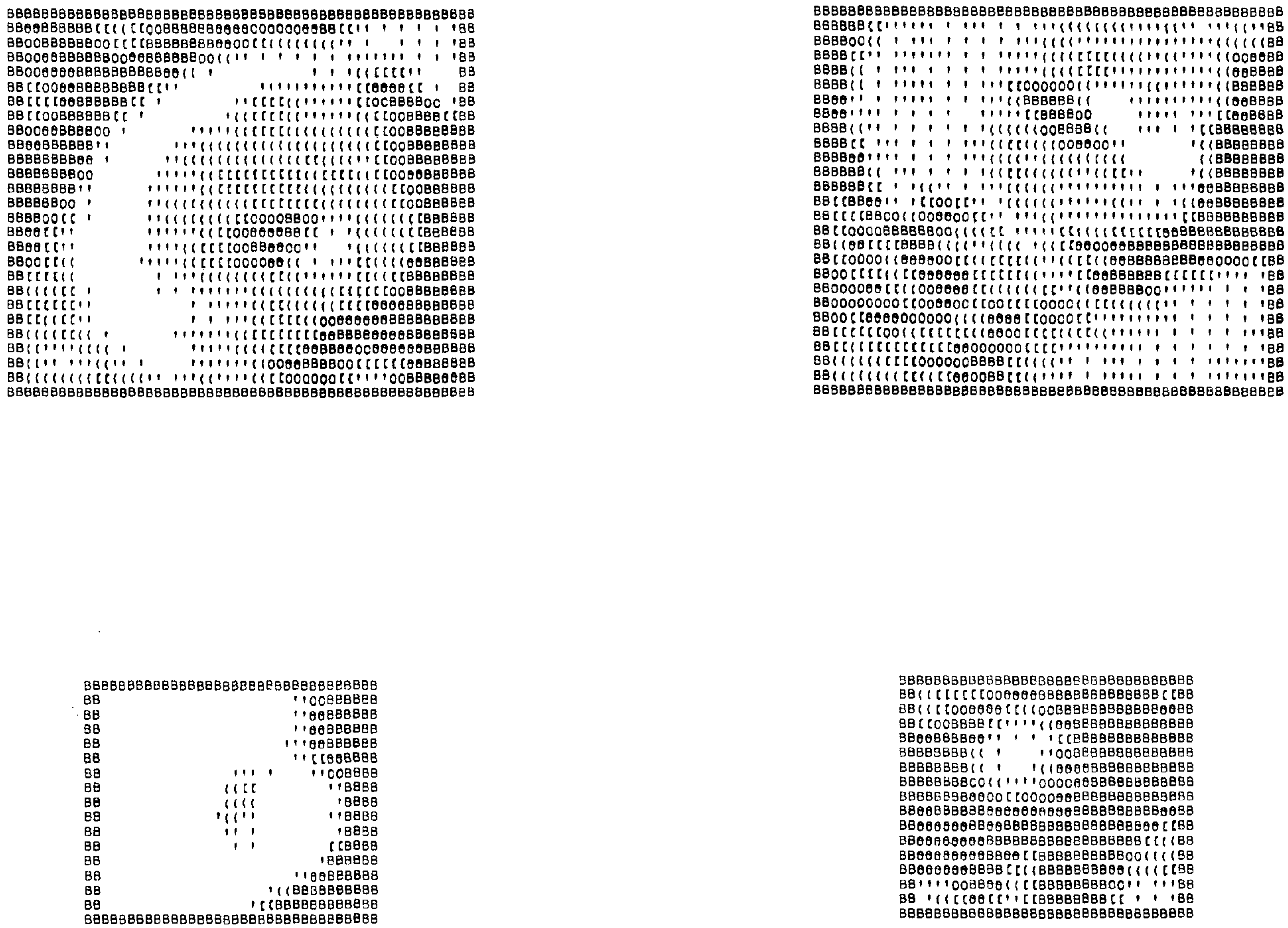
Figure 3. Craters Without Elevations



cz733

Figure 4. Craters With Elevations

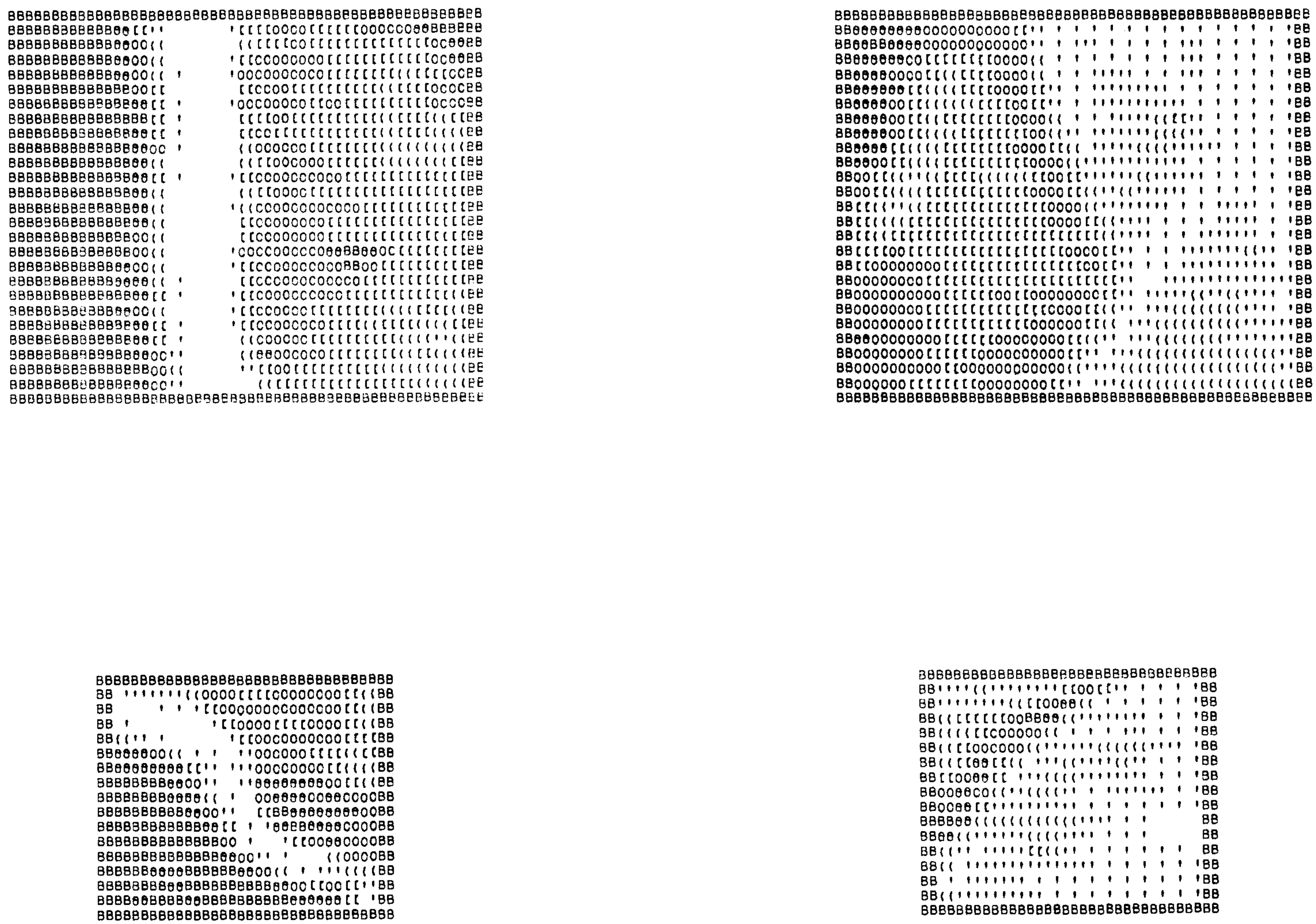


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Figure 5. Wrinkle Ridges

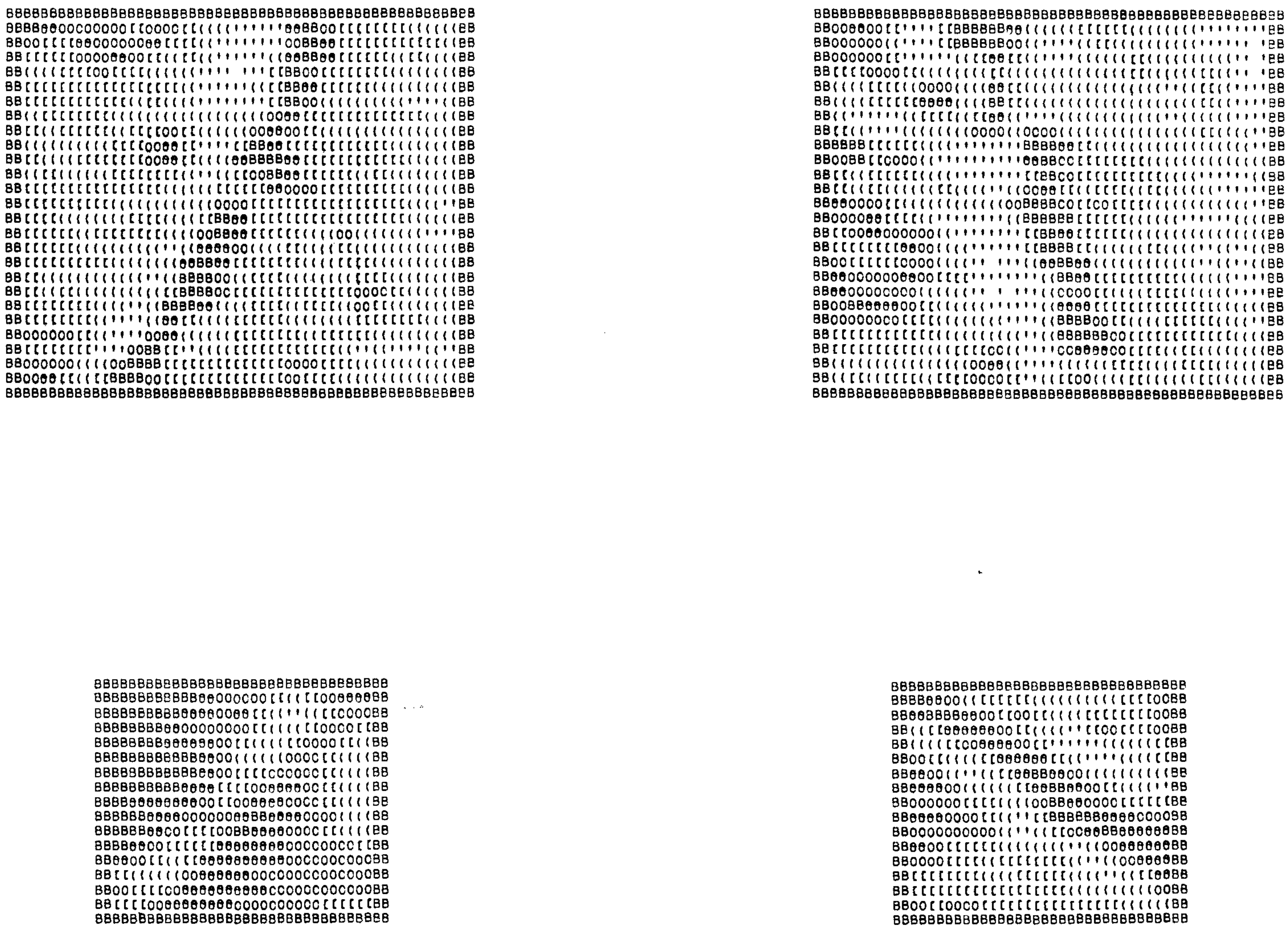

Figure 6. Rima

TABLE V

RIMA VS. RIDGES (25 x 25), 260 QSID UNITS

Technique	Classification %	Generalization %
Forced Learning	75.50	65.25
Bayes Weights	75.45	65.25

	Total Cycles	For Best Classification			For Best Generalization		
		Class. %	Gen. %	Cycles	Class. %	Gen. %	Cycles
Error Correction	194	100.00	75.50	194	95.60	76.00	72
Iterative Design	6	100.00	73.50	6	99.30	75.75	2
MADALINE	41	100.00	73.75	41	88.65	77.00	3

yield marginally better generalization results. With the recursive techniques, generalization performances are all at least as good as the 75.75 percent achieved earlier on the 50 by 50 patterns, but the maximum 77 percent is not significantly better.

Table VI presents the results obtained on the RvR task using the 15 by 15 aperture. These networks used 235 property filters. Generalization performances showed a more substantial improvement, reaching a level of 84.5 percent with the MADALINE technique. Using the Iterative Design technique, decision functions were derived for the first 180, 190, 200, 210, 220, and 230 property filters in this set. Two hundred ten property filters were enough to provide complete separation of the training patterns. The best generalization performance was obtained with 180 property filters, which gave 79.75 percent correct decisions — an improvement of one percent.

The results on Task CvC show more dramatic improvements than on Task RvR. This is no doubt partially due to the quadratic effect on crater patterns of aperture reduction as opposed to the linear effect on ridges and rima noted earlier. Part of the difference probably stems from the better quality of the crater patterns. Poorer initial performance (63.75 percent on the 50 by 50 patterns) also helps to underscore the improvement. Table VII presents the results achieved with the 25 by 25 aperture. Two systems achieve 82.5 percent on the generalization patterns. These results are based on the full set of 140 property filters used by the QSID program to achieve complete separation. Using the Iterative Design technique, the effectiveness of smaller sets of property filters was investigated. Figure 7 presents the classification and generalization error percentages as a function of the number of property filters used. In each case, the property filter subsets represented an initial segment — the set of 100 units, for example, being the first 100 property filters designed by the QSID program. The curves of Figure 7 are apparently typical. A limited reduction in the property filter set produces a slight improvement in the generalization performance (in this case, 120 units give 83.25 percent). The most reasonable explanation for this phenomenon is that near the end of a QSID run, only a very small number of patterns influence the selection of the property filters. Lacking the statistical defense of numbers, the last property filters selected most likely are based on the individual noise

TABLE VI

RIMA VS. RIDGES (15 x 15), 235 QSID UNITS

Technique	Classification %	Generalization %
Forced Learning	84.70	83.25
Bayes Weights	84.85	82.75

	Total Cycles	For Best Classification			For Best Generalization		
		Class. %	Gen. %	Cycles	Class. %	Gen. %	Cycles
Error Correction	138	100.00	77.75	138	84.05	80.50	11
Iterative Design	7	100.00	78.75	7	100.00	78.75	7
MADALINE	38	100.00	78.00	38	88.20	84.50	4

TABLE VII

CRATERS VS. CRATERS WITH ELEVATIONS (25 x 25), 140 QSID UNITS

Technique	Classification %	Generalization %
Forced Learning	87.90	63.75
Bayes Weights	87.75	63.75

	Total Cycles	For Best Classification			For Best Generalization		
		Class. %	Gen. %	Cycles	Class. %	Gen. %	Cycles
Error Correction	65	100.00	81.50	65	89.00	82.50	21
Iterative Design	9	100.00	82.25	4	99.90	82.50	3
MADALINE	15	100.00	80.00	15	99.90	80.75	13

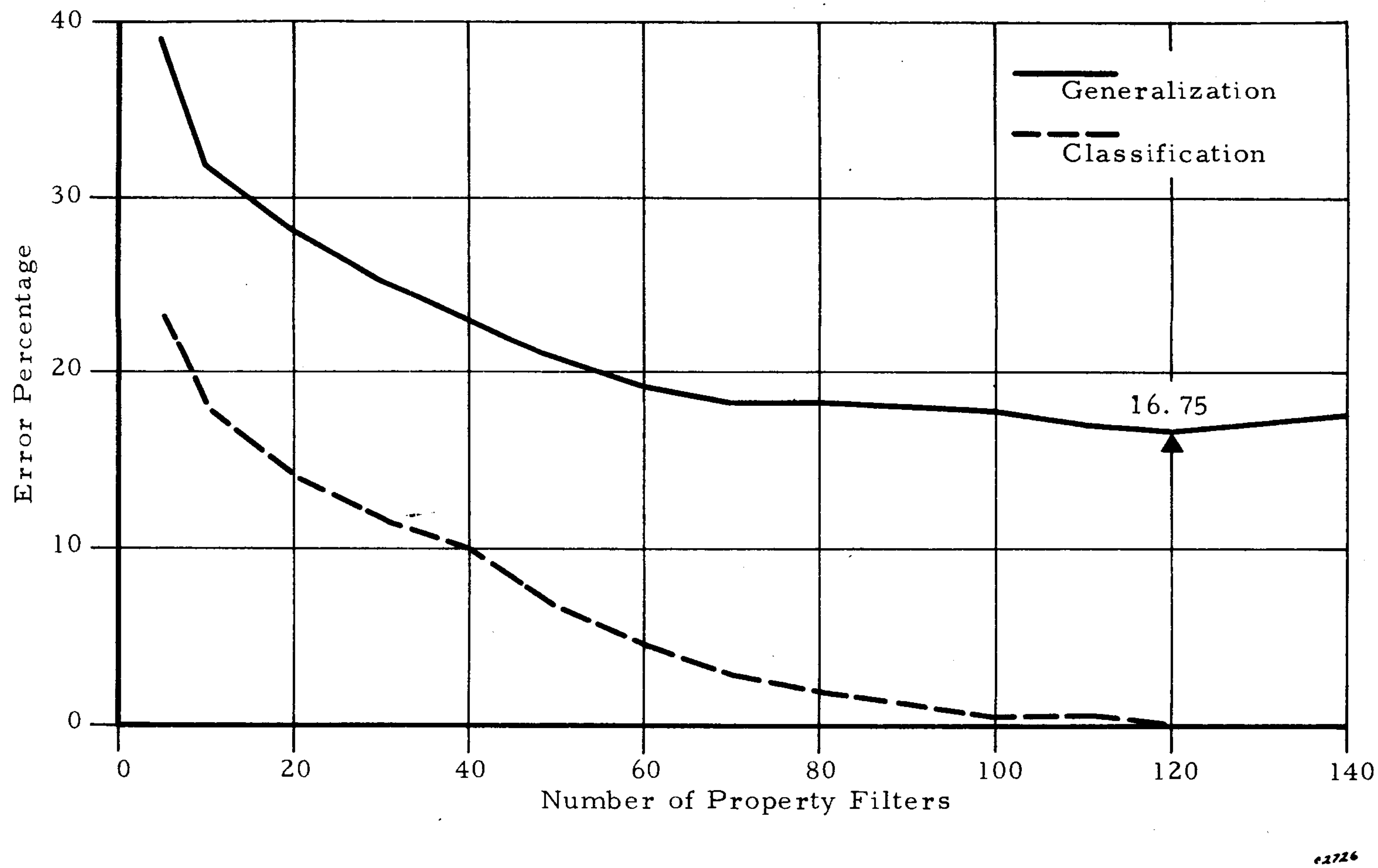

Figure 7. Craters vs. Craters With Elevations (25 x 25)

characteristics of the remaining patterns. Even with the reduced aperture, the central elevations occupy less than five percent of the input field.

When the aperture is reduced to 15 by 15, another large increase in performance is noted. Only 65 property filters are needed to produce the 96.25 percent performance given in Table VIII. Figure 8, which shows the effect of using smaller sets of property filters, does not indicate any improvements over the full set of units.

3.4 Summary

For patterns such as the lunar data, reducing the aperture size for small features is an effective technique. Using this method, performance on Task RvR was increased from 75.75 to 84.5 percent, and on Task CvC from 63.75 to 96.25 percent.

Results obtained using artificial noise-free patterns for training a system were not encouraging. Indications are that extreme care is necessary in defining the variations of the artificial patterns so that they are representative of the real patterns.

A study of the very high performance system designed for Task CvR indicates that this system does actually recognize patterns of both classes, and not the presence or absence of patterns of one of the classes.

TABLE VIII

CRATERS VS. CRATERS WITH ELEVATIONS (15 x 15), 65 QSID UNITS

Technique	Classification %	Generalization %
Forced Learning	96.70	87.75
Bayes Weights	96.80	87.75

	Total Cycles	For Best Classification			For Best Generalization		
		Class. %	Gen. %	Cycles	Class. %	Gen. %	Cycles
Error Correction	40	100.00	91.00	40	100.00	91.00	40
Iterative Design	8	100.00	96.25	4	100.00	96.25	4
MADALINE	26	100.00	93.75	26	99.90	95.00	19

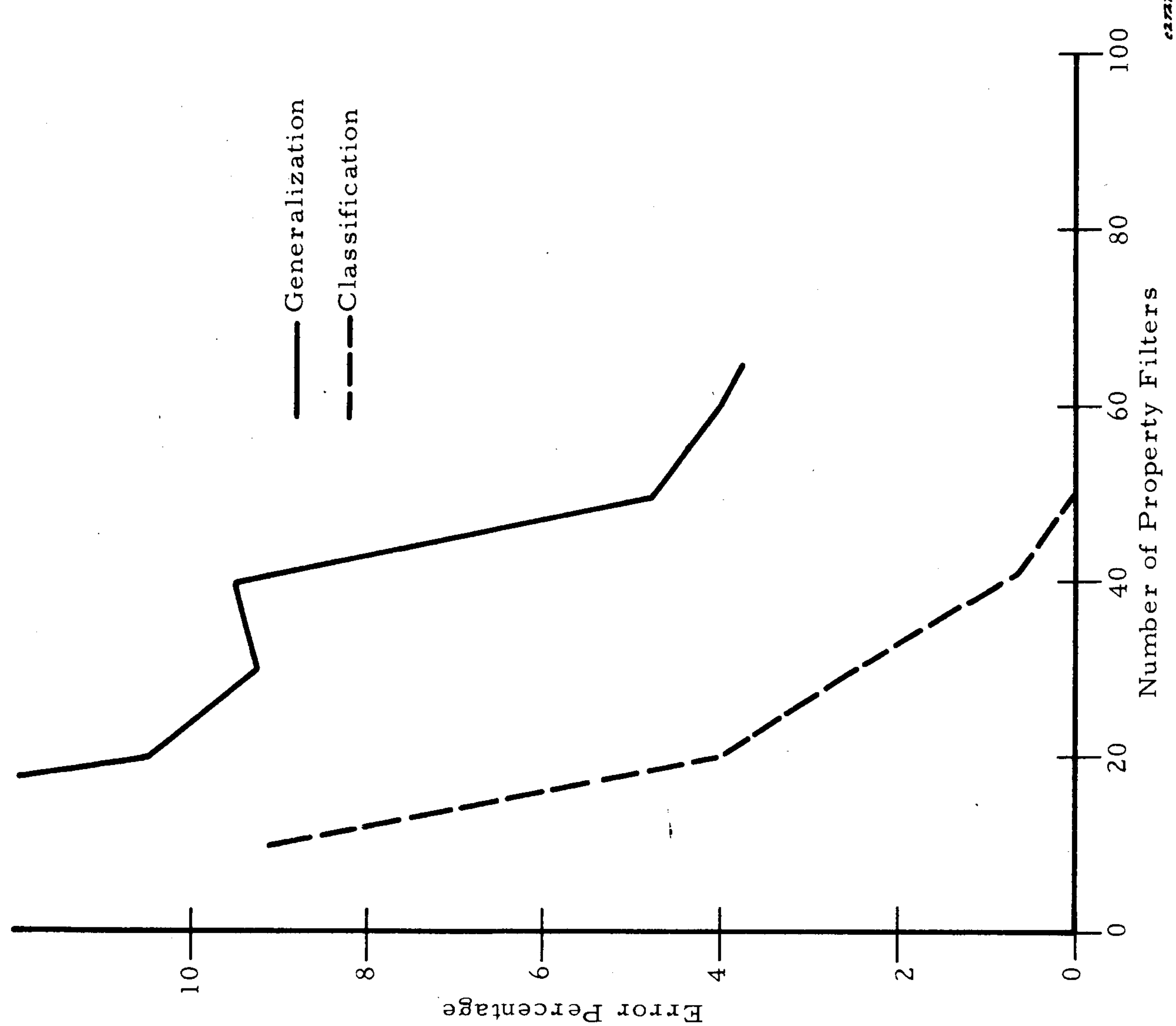

Figure 8. Craters vs. Craters With Elevations (15 x 15)

4.0 NIMBUS PATTERNS

4.1 Introduction

The three classes of NIMBUS patterns differ from the lunar patterns in that they are textural — there is no specific feature which may be centered in the aperture. The aperture size was selected to be large enough to insure that the textural nature was present in the pattern. Thus the cumulus patterns contain a substantial number of cloud cells. A 75 by 75 raster was used to provide adequate definition of the individual cloud cells. Reduction of the aperture size would destroy some of the textural quality of these patterns.

Generalization performances of 86.2 and 85.5 percent correct classification were achieved for Tasks NvC (noncumulus vs. cumulus) and PvS (polygonal vs. solid cell) respectively. Using the multilook technique described in Technical Report 3, summarized in Section 2 of this report, these figures were improved to 92.0 and 89.0 percent respectively. These latter figures are felt to approach the level of a human observer.

In a parallel effort, Mr. E. M. Darling, NASA technical officer on this project, produced a set of 29 logically designed properties (called "known properties" in this report). These properties are listed in Table IX. The property filters have multivalued outputs. Using a technique called Screening Multiple Regression to design a linear decision function on these properties, 89.7 percent generalization on Task NvC (using 3 of the properties) and 92.5 percent on Task PvS (using 4 other properties) were obtained.

The additional experiments on the NIMBUS data described in this section are based on these known properties. Section 4.2 describes results obtained using these properties with alternate techniques for assigning decision functions. Section 4.3 is concerned with augmenting the known property list with statistically designed property filters. A few miscellaneous results achieved on Task 8 of this project are given in Section 4.4.

4.2 Known Properties

Two techniques for assigning decision functions were applied to the entire set of 29 known properties for each of the two tasks. These were

TABLE IX

KNOWN PROPERTY LIST

1.	Mean Brightness		15.	Mean Cloud Segment	
2.	Brightness Variance		16.	Number of Clouds	
3.		0	17.	Mean Cloud Size	
4.		1	18.	Variance Cloud Size	
5.	Relative	2	19.		1-25
6.	Frequency	3	20.		26-100
7.	of Each	4	21.		101-225
8.	Gray Level	5	22.	Relative	226-400
9.		6	23.	Frequency	401-900
10.		7	24.	of Cloud	901-1600
11.	Information in the X-Direction (adjacent points)		25.	Size	1601-2500
12.	Information in the Y-Direction		26.		2501-3600
13.	Mean Gray Level Area (connected regions of constant gray level)		27.		3601-4900
14.	Variance, Gray Level Area		28.		4901-5625
			29.	.80 contour area (autocorrelation function)	

the Iterative Design technique rewritten to accept continuous inputs from the property filters, and the QSID technique itself. In this latter method, the known properties are followed by a layer of statistically designed quadratic-input, binary-output property filters, which in turn is followed by a linear decision function. The resultant decision boundary in the known property space is a quadric (piecewise-quadratic).

Since the known properties are virtually independent of rotations or small translations, only the basic patterns were used. There were totals of 342 training and 101 generalization patterns for Task PvS, and 510 training and 159 generalization patterns for Task NvC.

Table X presents the results for Task PvS. The Screening Multiple Regression results, and the best multilook generalization results are given to provide a reference. Using all 29 property filters, Iterative Design was able to achieve a remarkable 97.0 percent generalization. QSID almost matched this, with 96.3 percent generalization, while at the same time achieving complete separation of the training patterns. The performance of the Iterative Design system for the expanded pattern set is also given. The expanded set consists of the 2000 training and 400 test patterns used in the earlier work and in Section 4.3.

Table XI presents similar results for Task NvC. In this case, Iterative Design and QSID using 29 properties achieve only nominal increases in performance, to 90.6 and 91.0 percent respectively, in comparison with the Screening Multiple Regression using 3 properties. With more statistical properties, QSID can achieve complete separation of the training patterns, but the generalization performance falls back slightly to 90.6 percent. The more pronounced performance variation in passing to the expanded pattern set on Task NvC is due to the uneven expansion of the classes, the noncumulus class requiring twice the expansion of the cumulus class.

4.3 Augmentation of Known Properties

For the two tasks, the set of 29 known properties was augmented by statistically derived properties, selected to complement the function of the known properties. The decision functions derived by Iterative Design on the known properties formed the basis for the augmentation. The portions of the

TABLE X

SOLID CELL VS. POLYGONAL CELL
29 KNOWN PROPERTIES

Decision Mechanism	Classification	Generalization
Reference Multi-Look 400 Statistical Props.		89.0
Reference Screening Multiple Regr. 4 Known Properties	91.4	92.5
Iterative Design	94.7	97.0
Iterative Design Expanded Pattern Set	93.3	97.0
QSID	100.0	96.3

TABLE XI

CUMULUS VS. NONCUMULUS
29 KNOWN PROPERTIES

Decision Mechanism	Classification	Generalization
Reference Multi-Look 400 Statistical Properties		92.0
Reference Screening Multiple Regr. 3 Known Properties	86.7	89.7
Iterative Design	88.2	90.6
Iterative Design Expanded Pattern Set	86.0	90.0
QSID	92.1	91.0

linear decision functions using the known properties were fixed. Pattern losses for the expanded pattern sets were derived, and used as initializations for the QSID program. Due to these initializations, property filters selected by QSID are directed towards the unsolved portions of the tasks, since selections are based on reduction of the system loss. 70 of these add-on property filters were required by QSID for complete separation of the training patterns on Task PvS, and 150 add-on units were required on Task NvC.

Following the design of the add-on units, the linear decision functions designed by QSID for these units were discarded. The portions of the decision functions for the known properties were again held fixed, and those for the add-on units reassigned using Iterative Design. This was also done for various sized subsets of the add-on property filter sets, choosing initial segments for the subsets.

The results for Task PvS are given in Figure 9. For the known properties alone 3 percent generalization errors are made. With any substantial number of add-on units in the system, approximately a 6 percent error rate occurs. Best performance with any add-on units occurs with one unit, giving a 3.75 percent error rate. It is likely that with the high level of performance achieved by the known properties alone, the add-on units were identified with the individual noise patterns of the few remaining patterns.

Figure 10 presents the results for Task NvC. For the known properties alone, a 10 percent generalization error rate is obtained. The best performance with add-on units occurs with 90 add-on units, and gives 7.25 percent errors on the test patterns.

Performance of the known properties on Task PvS was very high, and augmentation of these units resulted in deterioration of the generalization results. The known properties yielded lower performance on Task NvC, and augmentation provided some improvement in generalization. It seems likely that the poorer the performance of the known properties, the more effective the add-on units will be. Further testing of this will be accomplished in the coming quarter, when add-on units will be designed for 15 known properties applied to the lunar data at all three aperture sizes.

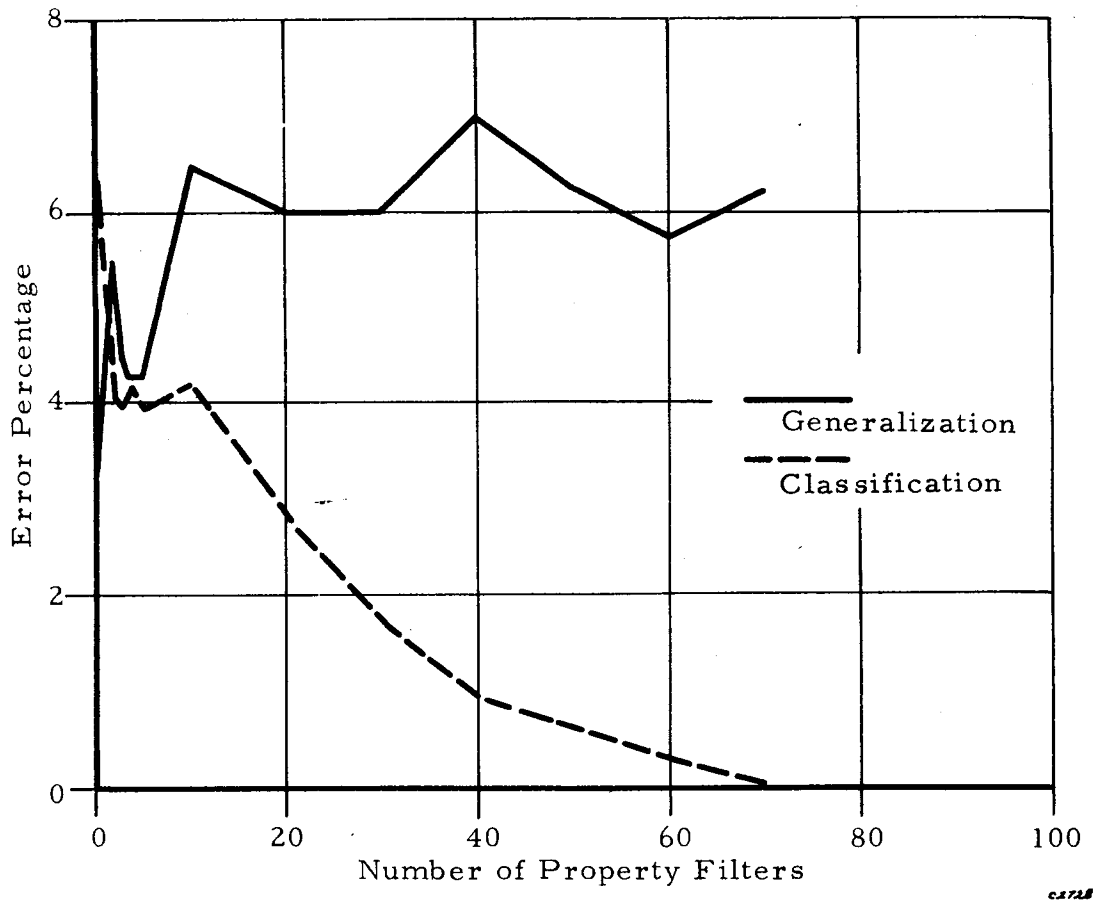

Figure 9. Solid Cell vs. Polygonal Cell Add-On Units

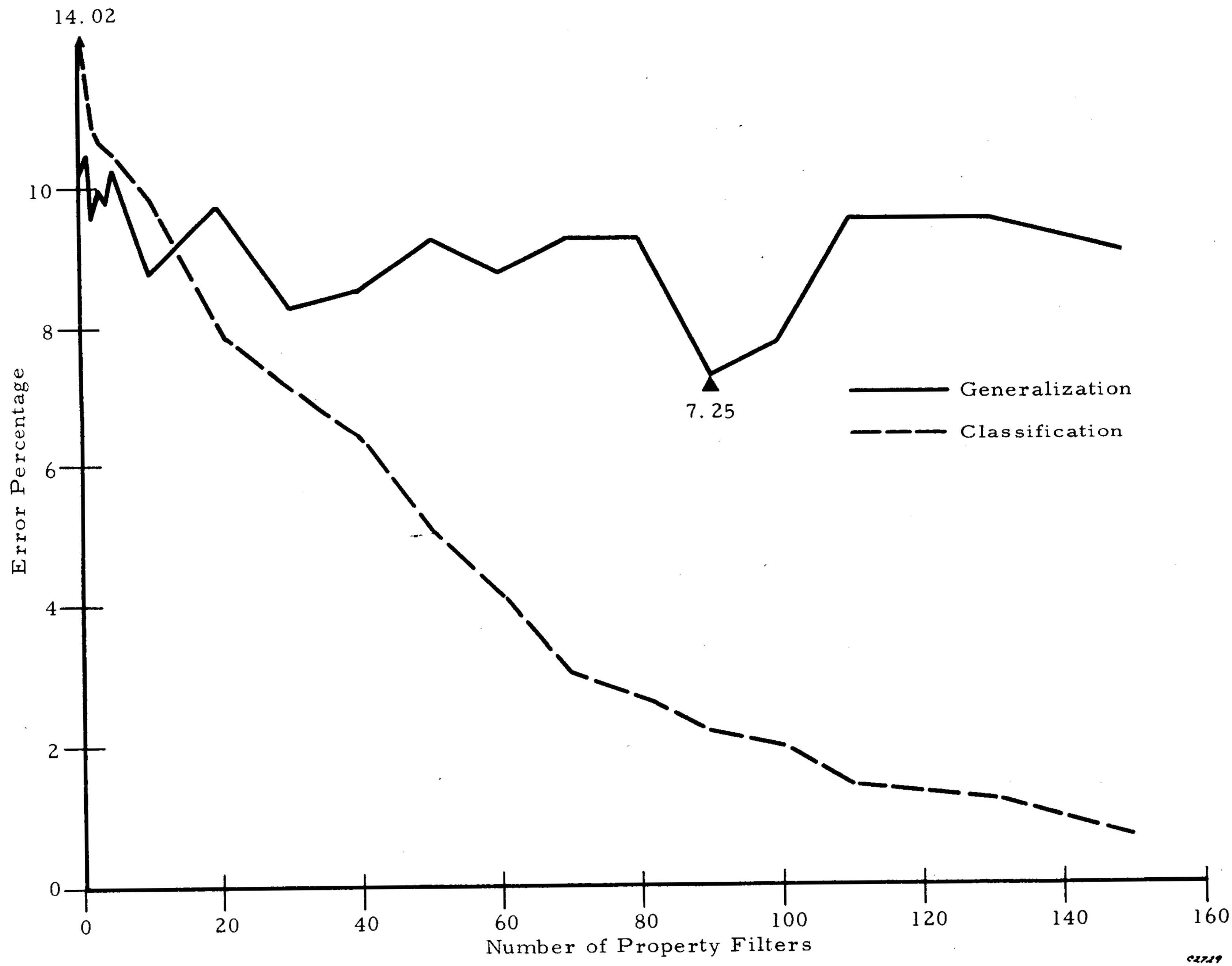

Figure 10. Cumulus vs. Noncumulus Add-On Units

4.4 Miscellaneous Experiments

Two alternative procedures for designing decision functions have been applied to the statistically derived 400 property filter sets for the NIMBUS data. This represents preliminary work on Task 8 of this project, and the experiments are far from comprehensive. More detailed descriptions of the techniques and the training algorithms will be given in the next technical report.

For Task PvS, a modified Fix and Hodges technique was applied. For each generalization pattern, the nearest (in terms of property profile) 45 training patterns were determined, and the class most represented in these 45 patterns determined the system decision. The technique modification consists of a training routine in which the weightings for the individual property filter's contribution to the distance function are determined. Although this technique has worked well on other pattern recognition tasks, in this instance it achieved only 82.75 percent generalization, compared to 85.5 for Iterative Design and MADALINE. Only one training cycle was used, which may account for the lower performance.

Piecewise Linear decision surfaces were generated for both tasks. In this technique, a number of linear functions are assigned to each class. A training algorithm determines the coefficients for each linear function. When a generalization pattern is tested, the linear function having the largest value determines the system decision. On Task PvS, systems with 2 and 4 functions per class were designed, giving generalization performances of 87.5 and 85.25 percent respectively. On Task NvC, 2, 4, and 6 functions per class were used, giving performances of 87.25, 88.0, and 88.5 percent respectively. On both tasks, Piecewise Linear machines bettered the performances achieved with the six techniques studied earlier.

4.5 Summary

The linear technique Iterative Design and the quadric technique QSID provide virtually identical generalization performance when used to assign a decision function to the known properties, with QSID yielding much higher classification performances. These techniques gave a nominal increase in generalization on Task NvC and a substantial increase on Task PvS in comparison with Screening Multiple Regression, which uses only 10 to 15 percent of the known property filters.

On Task PvS, where performance with the known properties is very high, the augmentation of the known properties with statistically derived properties actually lowers the performance level. On Task NvC, where performance with the known properties was good, but not as good as on Task PvS, the augmentation resulted in improved performance.

5.0 PROGRAM FOR THE NEXT PERIOD

During the next reporting period, effort will be concentrated on Items 7 and 8 of the contract — to develop new, and improve existing, methods for the extraction of pattern features and for the design of decision mechanisms. In addition work on Item 4c, the application and augmentation of known properties to the lunar data, will be completed now that the property profiles have been received. Efforts are now underway on about half of the subtasks on Items 7 and 8.

A pilot program for selecting property subspaces using an entropy function will be modified to accommodate higher dimensional data. A program for selecting subspaces using iterative design is partially written. Property filters will be designed in these subspaces using iterative design and using distribution estimation with cluster analysis. Experiments which may lead to optical processing for the design of feature extraction are in the preliminary stages. These efforts will be completed in the coming quarter.

Experiments using the nonlinear Fix and Hodges, and Piecewise Linear techniques for decision mechanisms are in progress. Preliminary results are given in this report. Other nonlinear techniques will be sought. A modified MADALINE routine has been blocked out. Distribution estimation with cluster analysis will also be used to design decision functions. Attempts to optimize and improve other previously described decision mechanism algorithms will be made. This work will also be completed in the coming quarter.